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Publication date:
2006

Document version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Sauer, J., & Balint, B. (2006). *Romanian maize: distorted prices and producer efficiency*. Fødevareøkonomisk Institut, Københavns Universitet. IFRO Working Paper Vol. 2006 No. 2

Download date: 04. May. 2023

Romanian Maize – Distorted Prices and Producer Efficiency

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Abstract

This research aims at shedding empirical light on the relative efficiency of small-scale maize producers in Romania. Farmers in transition countries still face heavily distorted price systems resulting from imperfect market conditions and socioeconomic and institutional constraints. To capture such distortions we formulate a stochastic shadow-cost frontier model to investigate the systematic input-specific allocative inefficiency. We further adjust the underlying cost frontier by incorporating shadow price corrections and subsequently reveal evidence on farm specific technical inefficiency. Different models are estimated due to the imposition of curvature correctness and the effects on the individual efficiency estimates are shown. The empirical results show a relative high technical efficiency of the small-scale farmers but relatively poor scores on systematic input price efficiency. The usage of extension services as well as agricultural training on the farm level are found to have a positive effect on the technical efficiency level of the farms. All model specifications further agree on the negative effect on efficiency with respect to the use of insecticides. The imposition of functional concavity on the shadow cost frontier leads to relative differences in the efficiency estimates of up to 240%.

KEY WORDS *Efficiency, Shadow Cost Frontier, Functional Consistency, Maize, Romania*
Jel *C40, D24, O33*

Contents

Preface

This research work has been done by assistant professor Johannes Sauer and senior researcher Balint Borbala, Center for Development Research, University of Bonn, Germany.

Professor Peter Bogetoft has reviewed the paper and secretary Inger Sommer edited the final version.

Institute of Food and Resource Economics
Production and Technology Division, January 2006

Mogens Lund

1. Introduction

Profound structural changes are still taking place in the process of transition from a command to a market oriented economy in Romania. This is especially true for the agricultural sector where the structural reforms are concentrated on the privatization of land and the downsizing of agricultural enterprises and led to the emergence of numerous small farms (Lerman 1999, OECD 2000). These farmers – so-called individual farmers – are currently the most important actors with respect to land and output markets (OECD 2000, Leonte 2002). However, they are still heavily constrained with respect to an insufficient factor endowment and the lack of developed input and output markets. As a result, most technology intensive crops have been substituted by the cultivation of more traditional crops and the importance of subsistence farming increased (Tesliuc 2000).

The production of maize as one of the main traditional crops in Romania increased in its importance which is also related to its relatively simple way of production and storage (Tesliuc 2000). Hence, this crop currently plays a central role in agricultural production being cultivated on a relatively large territory and providing a relative large proportion of output (NIS 2004). Due to Gorton et al (2003) maize shows a comparative advantage in Romania. Given this importance of maize production for agricultural transition and rural development in Romania this research aims to assess the relative efficiency of small-scale maize production and tries to determine different factors for maize farms' inefficiency. To the background of the restructuring in the Romanian agriculture the individual farmers' decisions are often made with respect to shadow prices as the prices the decision maker actually has to pay rather than those observed as prevailing market prices (see Toda 1976, Atkinson and Halvorsen 1980, Kumbhakar and Bhattacharyya 1992 and Wang et al. 1996). The following study therefore uses such shadow prices to model and analyze the relative efficiency of small-scale Romanian maize producers. With respect to policy relevant empirical based productivity studies Gorton and Davidova realized in 2001 that "(…) there is a lack of evidence on the Baltic States and Romania." This lack still exists with respect to Romanian agricultural production.

After briefly outlining the case of small-scale maize production in Romania subsequently the applied model is described as a combination of the shadow price approach to reveal systematic allocative efficiency and the error components approach to obtain producer specific technical efficiency estimates. The estimated models are tested and corrected for theoretical consistency and further bootstrapping techniques are applied to investigate the statistical robustness of the most consistent model. Finally the relative efficiency scores and possible factors for their variance over the sample are discussed.

2. The Case Study – Small-Scale Maize Production in Romania

The majority of the restructuring measures in the Romanian agricultural sector since 1989 were concentrated on the privatization of land aiming at changing collective agriculture to individual agriculture as well as on the downsizing of the farms (Lerman 1999). The future owners could choose among the following options: individual farming, joining a family based association, joining a formal association, and pursuing a mixed strategy (Sabates-Wheeler 2001). The majority of farmers chose individual farming and thus, in 2002, 4.7 million individual farms cultivated 62% of the arable land with an average size of 1.6 hectares per farm (NIS 2004). However, by reestablishing the situation before collectivization, the privatization hence led to the fragmentation of the agricultural land and consequently the new individual farmers were constrained in their business development by the fragmented structure and small size of the land holdings. The farms could not be adjusted to their efficient size because the restituted land was banned from selling till the year 1998 and a simplification of the complex law on leasing was only conducted in the same year. Due to this structure the renting of agricultural land was not attractive to those farmers as obtaining a large piece of land implied substantial transaction costs as a consequence of the need for coordinating several different land owners (Tesliuc 2000).

Furthermore the new individual producers lacked the necessary know-how to cultivate their land. They had no cash to invest and rarely access to credit as well as agricultural equipment. Up and downstream sectors had not been restructured to suit the needs of the small farmers which led to high transactions costs by using the different input and output makets. Such transaction costs and the lack of capital reinforced the decline in the use of inputs like fertilizer and certified seed (Kenneth 2003, OECD 2000, Tesliuc 2000). By responding to these difficulties producers diversified their production, substituted commercial by non-commercial crops, technical crops by traditional crops and increased subsistence production. The latter finally further promoted the stagnation in the development of input and output markets and led to a kind of vicious circle. The increase in maize cultivation in Romania during this period is basically linked to these developments in the agricultural sector. Maize production is one of the traditional agricultural activities and the area devoted to increased from about 26% (1990) to about 36% (2003) of the arable land (NIS 2004). The cultivation of maize shows the relative advantage of low input intensity: no certified and commercially distributed seed is needed, the crop can be simply harvested by hand and easily stored without the need for sophisticated facilities. Maize can be consumed in the household as well as in the process of animal production. The latter leads finally to relatively less dependence on the purchase of additional fodder (Tesliuc 2000).

Although the economic reforms in Romanian agriculture have reduced direct state control over production decisions, various interferences in the input and output markets still distort farmers' production decisions. Despite some studies on the economic efficiency of farming in transitional countries (see e.g. Hughes 1998, Mathijs/Swinnen 2000) none considers the effects of distorted input and output price relations with respect to the relative efficiency of agricultural production in Romania. Due to the vast literature on shadow prices (see for an overview e.g. Khumbhakar/Lovell 2000) non-observable shadow price ratios have to be considered as the relevant ones for producer decisions in distorted agricultural markets. The divergence between the analysed (i.e. estimated) shadow prices and the observed market prices can be interpreted as the sum of allocative inefficiency due to the prevalence of various market constraints as well as optimization failure by the farm management. Different approaches to model this divergence can be found in the literature: The usual method consists of additively translating observed prices to create shadow prices. Alternatively shadow prices can be modeled by multiplicatively scaling observed prices into shadow ones (Lau/Yotopoulos 1971). We follow the latter approach here and define the relationship between the normalized shadow prices for the variable and fixed inputs w^*, f^* and the normalized market prices w, f as

$$w^*_i = \theta_i w_i \qquad f^*_l = \theta_l f_l \qquad [1]$$

where θ_i, θ_l are (non-negative) price efficiency parameters and i, l are indices for variable and fixed inputs respectively. If no bending market restrictions are the case then θ_i, θ_l equal unity, if market distortions restrict optimizing behaviour then $\theta \geq 0 \wedge \theta \neq 1$. Consequently, a Romanian maize farmer can be regarded as allocatively efficient with respect to observed market prices only if observed market prices reflect the farmer's opportunity cost with respect to inputs. It has to be considered that the price efficiency parameters θ_i, θ_l may reflect both effects of market distortions as well as optimization errors.

3. The Model – A Combination of Shadow Prices and Error Components

We start our modeling efforts by formulating a simple single-output translog cost function and its associated cost-minimizing input cost share equations (see e.g. Atkinson/Halvorsen 1980, Kumbhakar 1989, Wang et al., 1996, Kumbhakar-/Bhattacharyya, 1992):

$$\ln C(w,y,f,e;\alpha,\beta,\gamma,\delta,\chi) = \alpha_0 + \sum_{i=1}^{2}\alpha_i \ln w_i + \frac{1}{2}\sum_{i=1}^{2}\sum_{k=1}^{2}\beta_{ik}\ln w_i \ln w_k + \gamma_y \ln y$$
$$+\frac{1}{2}\gamma_{yy}(\ln y)^2 + \sum_{i=1}^{2}\beta_{yi}\ln y \ln w_i + \sum_{l=1}^{2}\delta_l \ln f_l + \frac{1}{2}\sum_{l=1}^{2}\sum_{m=1}^{2}\delta_{lm}\ln f_l \ln f_m + \sum_{i=1}^{2}\sum_{l=1}^{2}\delta_{il}\ln w_i \ln f_l$$
$$+\sum_{l=1}^{2}\delta_{yl}\ln y \ln f_l + \sum_{n=1}^{6}\chi_n \ln e_n$$

[2]

and

$$S_i(w,y,f;\alpha,\beta,\delta) = \alpha_i + \sum_{k=1}^{2}\beta_{ik}\ln w_k + \beta_{yi}\ln y + \sum_{l=1}^{2}\delta_l \ln f_l \qquad i=1,2 \qquad [3]$$

[3]

respectively, where symmetry and homogeneity of degree +1 in input prices are imposed through the parameter restrictions

$$\beta_{ik} = \beta_{ki},\ i \neq k,\ \sum_{i=1}^{2}\beta_i = 1,\ \sum_{k=1}^{2}\beta_{ik} = 0,\ k=1,2;\ \sum_{i=1}^{2}\beta_{yi} = 0$$

and where y = maize output; the variable inputs' prices w = labour, fertilizer; the quasi-fixed inputs f = land, organic fertilizer; and the control variables e = herbicide used, insecticides used, seed applied, subsidies received, extension services used, agricultural training received.

Incorporating shadow prices according to [1] and following the input-oriented approach with respect to technical efficiency, observed expenditure and observed input cost shares can be expressed in terms of shadow cost and shadow input cost shares as

$$\begin{aligned}\ln C = \alpha_0 - \sum_{n=1}^{6} \chi_n D_n + \gamma_y \ln y + \frac{1}{2}\gamma_{yy} (\ln y)^2 + \sum_{i=1}^{2} \alpha_i \ln(\theta_i w_i) + \frac{1}{2}\sum_{i=1}^{2}\sum_{k=1}^{2} \beta_{ik} \ln(\theta_i w_i) \ln(\theta_k w_k) \\ + \sum_{i=1}^{2} \beta_{yi} \ln y \ln(\theta_i w_i) + \sum_{l=1}^{2} \delta_l \ln(\theta_l f_l) + \frac{1}{2}\sum_{l=1}^{2}\sum_{m=1}^{2} \delta_{lm} \ln(\theta_l f_l) \ln(\theta_m f_m) \\ + \sum_{i=1}^{2}\sum_{l=1}^{2} \delta_{il} \ln(\theta_i w_i) \ln(\theta_l f_l) \\ + \sum_{l=1}^{2} \delta_{yl} \ln y \ln(\theta_l f_l) + \ln\left\{ \sum_{i=1}^{2} (\theta_i)^{-1} \left[\beta_i + \sum_{i=1}^{2} \beta_{ik} \ln(\theta_k w_k) + \beta_{yi} \ln y \right] \right\}\end{aligned} \qquad [4]$$

[4]

and

$$S_i = \frac{(\theta_i)^{-1} \left[\beta_i + \sum_{k=1}^{2} \beta_{ik} \ln(\theta_k w_k) + \beta_{yi} \ln y \right]}{\sum_{i=1}^{2} (\theta_i)^{-1} \left[\beta_i + \sum_{k=1}^{2} \beta_{ik} \ln(\theta_k w_k) + \beta_{yi} \ln y \right]} \qquad i = 1, 2 \qquad [5]$$

[5]

respectively, where symmetry and homogeneity of degree +1 in input prices are imposed as outlined above. Classical error terms are appended, one input cost share equation is deleted, and the remaining system of *I* equations is estimated. χ includes the relative technical inefficiency with respect to a group of farmers defined along different characteristics, θ gives the systematic allocative inefficiency for the respective input.

Different recent contributions point to the crucial importance of considering the consistency of the estimated frontier with basic microeconomic requirements as monotonicity with respect to inputs as well as concavity of the function (see e.g. Ryan/Wales 1998 and Sauer 2005). Monotonicity of the estimated cost function – i.e. positive first derivatives with respect to all input prices - holds as all variable inputs W and quasi-fixed inputs F are positive for all observations in the sample. The necessary and sufficient condition for a specific curvature consists in the definiteness of the bordered Hessian matrix as the Jacobian of the derivatives $\partial C / \partial w_i$ with respect to w_i and $\partial C / \partial f_l$ with respect to f_l: if $\nabla^2 C(y,w,f)$ is negative definite, C is concave, where ∇^2 denotes the matrix of second order partial derivatives with respect to the shadow translog cost model defined by [4]. The Hessian matrix is negative definite at every unconstrained local maximum. Hence, the underlying function is concave and an interior extreme point will be a global maximum. The condition of concavity is related to the fact that this property implies a quasi-concave production function and consequently a convex input requirement set (see in detail e.g. Chambers 1988). Hence, a point on the isoquant is tested, i.e. the properties of the corresponding production function are evaluated subject to the condition that the amount of production remains constant. With respect to the translog shadow cost function model curvature depends on the specific variable input price and quasi-fixed input bundle, as the corresponding Hessian **H** for our 4 input case shows:

$$H = \begin{pmatrix} h_{11} & h_{12} & h_{13} & h_{14} \\ h_{21} & h_{22} & h_{23} & h_{24} \\ h_{31} & h_{32} & h_{33} & h_{34} \\ h_{41} & h_{42} & h_{43} & h_{44} \end{pmatrix} \qquad [6]$$

where h_{ii} is given by

$$\frac{d^2C}{d(w_i, f_l)^2} = \frac{d}{d\ln(w_i, f_l)}\left(\frac{d\ln C}{d\ln(w_i, f_l)}\right) = (w_i, f_l)^{-2}\left(\beta(\delta)_{rr} + S_r(S_r - 1)\right)$$

[7]

for r = i, l and S_r as the cost share of input r, and h_{ij} is given by

$$\frac{d^2C}{d(w_i, f_l)^2} = \frac{d}{d\ln(w_i, f_l)}\left(\frac{d\ln C}{d\ln(w_k, f_m)}\right) = \left[(w_i, f_l)(w_k, f_m)\right]^{-1}\left(\beta(\delta)_{rs} + S_r S_s\right)$$

[8]

for r = i, l and s = k, m. Given a point x^0, necessary and sufficient for curvature correctness is that at this point $v'Hv \leq 0$ and **v’s** = 0 where **v** denotes the direction of change. For some input bundles concavity may be satisfied but for others not and hence what can be expected is that the condition of negative definiteness of the Hessian is met only locally or with respect to a range of input bundles. The respective Hessian is negative definite if the determinants of all of its principal submatrices are negative in sign (i.e. $D_j < 0$ where D is the determinant of the leading principal minors and j = 1, 2, …, n). Hence, with respect to our translog shadow cost model it has to be checked a posteriori for every input bundle that monotonicity and concavity hold. If these theoretical criteria are jointly fulfilled the obtained estimates are consistent with microeconomic theory and consequently can serve as empirical evidence for possible policy measures.

Concavity can be imposed on our translog shadow cost model at a reference point (usually at the sample mean) following Jorgenson/Fraumeni (1981) and Ryan/Wales (1998). By this procedure the bordered Hessian in [6] is replaced by the negative product of a lower triangular matrix **Δ** times its transpose **Δ'**. Imposing curvature at the sample mean is then attained by setting

$$\beta(\delta)_{rs} = -(\Delta\Delta')_{rs} + \alpha(\delta)_r \lambda_{rs} + \alpha(\delta)_r \alpha(\delta)_s \tag{9}$$

where r = i, l and s = k, m and λ_{rs} = 1 if r = s and 0 otherwise and $(\Delta\Delta')_{rs}$ as the rs-th element of ΔΔ' with Δ as a lower triangular matrix:

$$H = -(\Delta\Delta') = -\begin{pmatrix} d_{11}d_{11} & d_{11}d_{12} & d_{11}d_{13} & d_{11}d_{14} \\ d_{11}d_{21} & d_{12}d_{12} + d_{22}d_{22} & d_{12}d_{13} + d_{22}d_{23} & d_{21}d_{14} + d_{22}d_{24} \\ d_{11}d_{31} & d_{31}d_{12} + d_{32}d_{22} & d_{31}d_{13} + d_{23}d_{23} + d_{33}d_{33} & d_{31}d_{14} + d_{23}d_{24} + d_{33}d_{34} \\ d_{11}d_{41} & d_{41}d_{12} + d_{42}d_{22} & d_{41}d_{13} + d_{42}d_{23} + d_{34}d_{33} & d_{41}d_{14} + d_{24}d_{24} + d_{34}d_{34} + d_{44}d_{44} \end{pmatrix} \tag{10}$$

As our point of approximation is the sample mean all data points are divided by their mean transferring the approximation point to an (n + 1)-dimensional vector of ones. At this point the elements of **H** do not depend on the specific input price bundle. The estimation model of the normalized translog shadow cost frontier is then reformulated as follows:

$$\ln\left(\frac{C}{C'}\right)=\alpha_0-\sum_{n=1}^{6}\chi_n\left(\frac{D_n}{D_n^{'}}\right)+\gamma_y\ln\left(\frac{y}{y'}\right)+\frac{1}{2}\gamma_{yy}\ln\left(\frac{y}{y'}\right)^2+\sum_{i=1}^{2}\alpha_i\ln\left(\theta_i\frac{w_i}{w'_i}\right)$$
$$+\frac{1}{2}\sum_{i=1}^{2}\left(h_{ii}+\alpha_i-\alpha_i\alpha_i\right)\ln\left(\theta_i\frac{w_i}{w'_i}\right)^2+\frac{1}{2}\sum_{i=1}^{2}\sum_{k=1}^{2}\left(h_{ik}-\alpha_i\alpha_k\right)\ln\left(\theta_i\frac{w_i}{w'_i}\right)\ln\left(\theta_k\frac{w_k}{w'_k}\right)$$
$$+\sum_{i=1}^{2}\beta_{yi}\ln\left(\frac{y}{y'}\right)\ln\left(\theta_i\frac{w_i}{w'_i}\right)+\sum_{l=1}^{2}\delta_l\ln\left(\theta_l\frac{w_l}{w'_l}\right)+\frac{1}{2}\sum_{i=1}^{2}\left(h_{ll}+\delta_l-\delta_l\delta_l\right)\ln\left(\theta_l\frac{w_l}{w'_l}\right)^2$$
$$+\frac{1}{2}\sum_{l=1}^{2}\sum_{m=1}^{2}\left(h_{lm}-\delta_l\delta_m\right)\ln\left(\theta_l\frac{w_l}{w'_l}\right)\ln\left(\theta_m\frac{w_m}{w'_m}\right)+\sum_{i=1}^{2}\sum_{l=1}^{2}\left(h_{il}-\delta_i\delta_l\right)\ln\left(\theta_i\frac{w_i}{w'_i}\right)\ln\left(\theta_l\frac{w_l}{w'_l}\right)$$
$$+\sum_{l=1}^{2}\delta_{yl}\ln\left(\frac{y}{y'}\right)\ln\left(\theta_l\frac{w_l}{w'_l}\right)+\ln\left\{\sum_{i=1}^{2}\left(\theta_i\right)^{-1}\left[\alpha_i+\sum_{i=1}^{2}\left(h_{ik}-\alpha_i\alpha_k\right)\ln\left(\theta_k\frac{w_k}{w'_k}\right)+\beta_{yi}\ln\left(\frac{y}{y'}\right)\right]\right\}+\varepsilon_i$$

However, the elements of Δ are nonlinear functions of the decomposed matrix in [10], and consequently the resulting normalized translog model becomes nonlinear in parameters. Hence, linear estimation algorithms are ruled out even if the original function is linear in parameters. By this "local" procedure a satisfaction of consistency at most or even all data points in the sample can be reached. The transformation in [11] moves the observations towards the approximation point and thus increases the likelihood of getting theoretically consistent results at least for a range of observations (see Ryan/Wales 2000). However, by imposing global consistency on the translog functional form Diewert and Wales (1987) note that the parameter matrix is restricted leading to seriously biased elasticity estimates. Hence, the translog function would lose its flexibility. By a second analytical step we finally (a posteriori) check the theoretical consistency of our estimated model by verifying that the Hessian is negative semi-definite (i.e. functional concavity).

In a second step the behavioural (shadow price) cost function in its constrained and unconstrained version (eq. [4] and [11]) is 'adjusted' by the estimated shadow price parameters θ and hence corrected for systematic allocative inefficiency by using these shadow prices as direct arguments in the cost function. An adjusted cost frontier is then modeled by simply adding the error components

$$\xi_i=v_i+u_i \qquad [12]$$

and applying stochastic frontier techniques to obtain the shadow-cost frontier and finally estimates of relative cost efficiency on the farm level (see e.g. Coelli et al., 1998 and Khumbhakar/Lovell 2000). As the price efficiency parameters θ_i,θ_l reflect both allocative effects of market distortions as well as optimization errors the relative inefficiency measured by the adjusted cost frontier consists solely of technical inefficiency (systematic and/or farm specific).

The stochastic frontier decomposes the error term into a two-sided random error that captures the inefficiency component and the effects of factors outside the control of the farmer. The theoretical foundation of such a model was first proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). The two-sided random error is assumed to be identically and independently distributed with zero mean and constant variance and is independent of the one-sided error. The distribution of the inefficiency component of the error is assumed to be asymmetrical. Following Battesse and Coelli (1995), the maximum likelihood estimation for equation 1 is obtained from the following log-likelihood function:

$$\ln L = -\frac{N}{2}\ln\left(\frac{\theta}{2}\right) - \frac{N}{2}\ln\sigma^2 + \sum_{j=1}^{N}\ln\left[1 - F\left(\frac{\varepsilon_j\sqrt{\delta}}{\sigma\sqrt{1-\delta}}\right)\right] - \frac{1}{2\sigma^2}\sum_{j=1}^{N}\varepsilon_j^2 \qquad [13]$$

where L is the log-likelihood function, N is the number of observations and $F(.)$ is the standard normal distribution function. σ^2 is the overall standard deviation equal to the sum of the standard deviations of the two error terms and δ is the proportion of the overall error term that is explained by the one-sided error. Assuming the half-normal distribution of the one-sided error term, the relative efficiency score defined at the mean is given as:

$$E\left[\exp\left(-u_j\right)\right] = 2\left[\exp\left(-\delta\sigma^2/2\right)\right]\left[1 - F\left(\sigma\sqrt{\delta}\right)\right] \qquad [14]$$

The measurement of farm level efficiency requires the estimation of the non-negative one-sided error that also depends on the assumptions regarding the distribution of the two and one-sided error terms. Based on Battesse and Coelli (1988), the best predictor of the relative efficiency of farmer *i* is given as:

$$E\left[\exp\left(-u_j \backslash \varepsilon_j\right)\right] = \left[\frac{1 - F\left(\sigma_w - \delta\varepsilon_j/\sigma_w\right)}{1 - F\left(-\delta\varepsilon_j/\sigma_w\right)}\right]\exp\left(-\delta\varepsilon_j + \sigma_w^2/2\right) \qquad [15]$$

where $\sigma_w = \sqrt{\delta(1-\delta)\sigma^2}$. The likelihood function is expressed in terms of the variance parameters i.e. $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\delta = \sigma_u^2/\sigma^2$. By following a single-equation cost frontier approach on this estimation stage we are able to avoid the 'Greene'-problem with respect to the consistent specification of the individual error components (see Kumbhakar/Lovell 2000).

Systematic allocative input-specific efficiency measures as well as group-wise technical efficiency measures are obtained by the translog shadow cost model. Measures of technical efficiency on farm level result from the error components model and finally such of farm-specific radial cost efficiency measures are obtained by simple calculation. As we are also interested in the effects of imposing theoretical consistency on the translog cost frontier we investigate the relative effect of such correction by using the simple index formula

$$\frac{\left(eff_i^{in} - eff_i^{con}\right)}{eff_i^{in}} * 100 \qquad [16]$$

To test for the robustness of our estimates by the adjusted shadow cost model (based on [4] and [11]) we further apply a simple stochastic resampling procedure based on bootstrapping techniques (see e.g. Efron 1979 or Efron/Tibshirani 1993). This seems to be necessary as our cross-sectional data sample consists of a (rather) limited number of observations. If we suppose that ψ_n is an estimator of the parameter vector ψ_n including all parameters obtained by estimating [16] based on our original sample of 64 Romanian maize farmers $X = (x_1, ..., x_n)$, then we are able to approximate the statistical properties of ψ_n by studying a sample of 100 bootstrap estimators $\psi_n(c)_m, c = 1, ..., C$. These are obtained by resampling our 64 observations – with replacement – from X and recomputing ψ_n by using each generated sample. Finally the sampling characteristics of our vector of parameters is obtained from

$$\Psi = \left[\psi_{(1)m}, ..., \psi_{(100)m}\right] \qquad [17]$$

4. Data and Estimation

We use data on 64 maize farmers based on a survey among agricultural households in 15 Romanian villages in 2003. The sample villages were chosen by a multistage representative random sampling procedure focused on seven regions defined by historical borders, landscape structure and distance to relevant input and output markets. The overall survey focused on data for 2002 with regard to various outputs, inputs and other household characteristics. The most frequently produced crop was maize, cultivated by about 92% of the households and only less than a quarter of all households cultivated technical more demanding crops as sunflower, soya or sugar beet. Table 1 gives the summary statistics on the sample data:

Table 1. Descriptive Statistics

Variable	Mean	StdErr	Min	Max
Total Costs (in Euro)	285.728	641.857	11.01	3,626.525
Output Maize (in kg)	4,696.313	8,510.552	56	42,000
Price of Maize (in Euro/kg)	0.103	0.017	0.056	0.130
Quantity of Labour (in mandays/month)	563.125	314.864	15	1,506.286
Price of Labour (in Euro/mandays)	0.699	1.259	0.0138	6.399
Quantity of Fertilizer (in kg)	18.198	37.083	1.176	264.706
Price of Fertilizer (in Euro/kg)	0.187	0.052	0.004	0.320
Quantity of Land (in ha)	1.909	3.921	0.08	30
Quantity of Org. Fertilizer (in kg/ha)	3,527.145	7,202.45	0	34,188
Herbicides used (binary)	0.594	0.495	0	1
Insecticides used (binary)	0.937	0.244	0	1
Commercial Seed used (binary)	0.406	0.495	0	1
Subsidies received (binary)	0.297	0.460	0	1
Extension Services used (binary)	0.5	0.504	0	1
Training used (binary)	0.187	0.393	0	1

The total costs of maize production are used as the dependent variable for the cost function estimations. The total output of maize produced, the price of maize, and the prices for the variable inputs labour and fertilizer as well as the quantities of the fixed variables land and organic fertilizers are applied as explanatory variables. Land can be considered as quasi-fixed as due to the aforementioned inflexibilities in the land market it can not be expected to be adjusted in a short- or even mid-term perspective. Organic fertilizer can be considered as quasi-fixed as small-scale Romanian farmers can not be expected to flexibly adjust the size of their livestock production as a response to crop input needs. Further binary variables for the use of herbicides, insecticides, commercial seeds, received subsidies, extension services used, and finally agricultural training and advice received are applied. All monetary variables are in Euro.

The estimation procedure is as follows: In a first step the translog cost system given by (4) and (5) is estimated using the cost function as well as the cost shares s_i derived from the non-distorted translog cost function lnC to obtain estimates for the allocative efficiency parameters θ with respect to the individual inputs as well as group-wise technical efficiency effects χ. The estimates of the former are subsequently substituted in (4) and after adding the error components given by (12) in a second step the adjusted translog cost frontier is estimated by applying the usual decomposition formula given in (14) and (15) to obtain estimates of producer-specific technical efficiency. As we 'corrected' the cost frontier for price distortions the resulting efficiency estimates u are soleley technical ones. Finally producer- and input-specific estimates of cost efficiency are obtained by simple calculation using the estimates for θ and u. The two-stage model is estimated using a non-linear iterative seemingly unrelated regression (ITSURE) technique with symmetry and homogeneity conditions imposed. As Greene (2000) notes, the Oberhofer-Kmenta (1974) conditions are met for the SURE model, so efficient maximum likelihood estimates can be obtained by iterating the basic feasible generalized least square (FGLS) procedure. This two-stage model is then estimated again (model 2) by imposing curvature correctness (i.e. functional concavity) on the cost function in (11) by basically following the decomposition shown by (9). By this we go beyond similar modelling efforts (see Atkinson/Halvorsen 1980, Kumbhakar 1989, Kumbhakar/Bhattacharyya 1992, Wang et al. 1996) and also incorporate considerations on the consistency of the estimated frontier with basic microeconomic principles (i.e. cost minimisation). Finally the estimation results of the unconstrained and the constrained models are compared with respect to the relative differences in the individual efficiency scores.

5. Results and Discussion

All estimated cost systems show a relatively good overall fit with respect to the usual statistical criteria. However, in the unconstrained model I only 27% of all observations adhere to functional concavity contrasting to 80% in the constrained model II (see appendix). A trade-off between the statistical significance and the theoretical consistency of the estimated function as documented by earlier studies (see e.g. Sauer 2005) are not confirmed by the results here. The estimated shadow price parameters show a high significance over the models. Table 2 and 3 summarize the estimation results with respect to systematic input-specific allocative, producer-specific overall technical and producer- and input-specific cost efficiency.

Table 2. Systematic Input – Specific Allocative Efficiency

	Model I		Model II	
Efficiency[1]	Mean	Std. Err.[2]	Mean	Std. Err.
AE Labor	0.476	0.007***	0.320	0.010***
AE Fertilizer	0.138	0.006***	0.585	0.009***
AE Land	0.380	0.001***	0.503	0.001***
AE Organic Fertilizer	0.260	0.001***	0.292	0.001***

1: allocative efficiency estimates are parameter based: no min and max values are available.
2: *,**,*** significance at the 1, 5, and 10% level.

Table 3. Producer – Specific Technical and Cost Efficiency

	Model I				Model II			
Efficiency	Mean	Std. Err.[1]	Min	Max	Mean	Std. Err.	Min	Max
TE	0.938	0.074***	0.606	0.999	0.869	0.131***	0.488	0.999
CE Labour	0.447	0.035***	0.289	0.476	0.278	0.042***	0.156	0.320
CE Fertilizer	0.129	0.010***	0.084	0.138	0.509	0.077***	0.285	0.585
CE Land	0.357	0.028***	0.230	0.380	0.438	0.066***	0.245	0.503
CE Organic Fertilizer	0.244	0.019***	0.157	0.260	0.254	0.038***	0.142	0.292

1: *,**,*** significance at the 1, 5, and 10% level.

The systematic allocative efficiencies with respect to the inputs labour, fertilizer, land, and organic fertilizer were found to be moderately higher with respect to the constrained model II. However, in the unconstrained model the variable input labour shows the highest efficiency (about 48%) whereas the same holds for the use of the variable input fertilizer in the constrained model (about 59%). On the other side the lowest allocative efficiency was found for fertilizer in the unconstrained (about 14%) and for the quasi-fixed input organic fertilizer in the constrained model (about 29%). What can be generally concluded from these results is that price distortions prevail in the agricultural input markets for labour and inorganic fertilizer. Hence, the underlying modelling assumption that maize producers optimize their production decisions with respect to unobservable shadow price ratios does hold for the sample. This indicates that cost minimization based on observable market prices may be inappropriate, and thus, a model incorporating market distortions is more suitable in an agricultural transition context. The values for the shadow prices indicate that 'prices' actually paid by the farmers for the inputs used are far less than the observed market prices because of the existence of market distortions. These findings strongly suggest that there is a considerable gap between agricultural input market prices and farm input prices. Different factors could account for such a price gap with respect to labour and fertilizer: As the price for hired labour rises farmers tend to substitute family for hired labour. Due to a lack of data labour is used here as an aggregated measure consisting of hired and family labour, hence, an increasing amount of family labour leads to a decrease in the average individual shadow price at the farm level for the variable input labour. As with respect to fertilizer the price increases as a consequence of the availability of commercially produced and marketed high quality fertilizers in the market, the scope and demand for black market fertilizer increases also. Consequently the quantity of available 'underpriced' fertilizer increases leading to a lower shadow price for fertilizer with respect to the individual farmer. The estimated shadow parameters for the quasi-fixed inputs land and organic fertilizer show that the farms' resource endowment – i.e. land endowment as well as livestock size – crucially influences its relative allocative performance. In the case of land the evidence of the two models is mixed: for model I it was found evidence that increasing the amount of cultivated land leads to an increase in allocative efficiency, for model II the opposite holds. In the case of organic fertilizer the models show evidence for an efficiency gain as the farmers apply more of it in producing maize.

Based on the estimated allocative efficiency parameters from the first step, a maximum-likelihood estimate of the corrected cost frontier is obtained and a technical efficiency index is derived for both models. Table 4 and 5 contain the frequency distributions for the producer-specific technical efficiencies. The corresponding density distributions for both models are illustrated in the appendix by figure A1 and A2.

Table 4. Frequency Distribution – Producer – Specific Technical Efficiency I				
		MODEL I		
EFFICIENCY INDEX	FREQUENCY[1]	PERCENTAGE	CUMULATIVE FREQUENCY	CUMULATIVE PERCENTAGE
0.6 – 0.7	1	1.56	1	1.56
0.7 – 0.8	2	3.12	3	4.69
0.8 – 0.9	9	14.06	12	18.75
0.9 – 1.0	52	81.25	64	100
Mean	0.938			
St.Err.	0.074***			
Min	0.606			
Max	0.999			

1: *,**,*** significance at the 1, 5, and 10% level.

Table 5. Frequency Distribution – Producer – Specific Technical Efficiency II				
		MODEL I		
EFFICIENCY INDEX	FREQUENCY[1]	PERCENTAGE	CUMULATIVE FREQUENCY	CUMULATIVE PERCENTAGE
0.4 – 0.5	1	1.56	1	1.56
0.5 – 0.6	4	6.25	5	7.81
0.6 – 0.7	4	6.25	9	14.06
0.7 – 0.8	6	9.37	15	23.44
0.8 – 0.9	9	14.06	24	37.50
0.9 – 1.0	40	62.50	64	100
Mean	0.869			
St.Err.	0.131***			
Min	0.488			
Max	1.000			

1: *,**,*** significance at the 1, 5, and 10% level.

The mean of the estimated technical efficiency is about 94% (model I) and about 87% (model II) whereas the least technically efficient farm shows a value of about 61% (model I) and about 49% (model II). This implies that at average up to 13% of the profit is lost due to technical inefficiency which is rather moderat compared to the revealed levels of allocative inefficiency. The frequency distributions of the individual farm's technical efficiency indices show that there is a moderate variation in the level among the farms in the sample: For both models the majority of farmers show a relative technical efficiency of more than 90% (see also figure A1 and A2). Based on the estimated systematic input-specific allocative efficiency as well as the estimated producer-specific technical efficiency finally producer- and input-specific cost efficiency levels are computed (see table 3). With the exception of labour the cost efficiency levels are moderately higher for the constrained model (model II) compared to those for the unconstrained model (model I). For model I maize farmers most efficiently used the variable input labour and on the other side least efficiently the variable input fertilizer with respect to costs. For model II farmers in the sample most efficiently used fertilizer and least efficiently the quasi-fixed input organic fertilizer. These cost efficiency results hence reveal partly mixed evidence for the different model specifications.

With regard to the effects of different production settings, institutional as well as policy related factors both estimation stages by construction delivered evidence, either with respect to groups of producers defined along such factors (shadow cost estimation stage) or with respect to individual producers (error components estimation stage). In the latter case the derived farm-specific efficiency index facilitates the decomposition of the efficiency performance at the individual maize farm level and allows for the identification of the factors that influence farmers' efficiencies. Table 6 and 7 summarize the different effects found.

Table 6. Group – Wise Technical Efficiency Effects

	Model I		Model II	
Factor	Mean	Std. Err.[1]	Mean	Std. Err.
TE Difference Herbicide	-0.024	0.011**	-0.042	0.016***
TE Difference Insecticide	-0.022	0.014	-0.008	0.020
TE Difference Seed	-0.013	0.009	-0.024	0.013*
TE Difference Subsidies	+0.018	0.007**	-0.036	0.038
TE Difference Extension	+0.025	0.009***	+0.051	0.015***
TE Difference Training	+0.029	0.013**	+0.087	0.019***

1: *,**,*** significance at the 1, 5, and 10% level.

Table 7. Producer – Specific Technical Efficiency Effects

FACTOR	MODEL I[1,2]	MODEL II
HERBICIDE	-*	+**
INSECTICIDE	-***	-***
SEED	-	+
SUBSIDIES	-	-***
EXTENSION	-***	-***
TRAINING	-***	+*

1: *,**,*** significance at the 1, 5, and 10% level.

The results for the shadow frontier show that the use of herbicides, the use of insecticides, and the application of commercial seeds are negatively correlated with the technical efficiency of the maize producing farms for both models. The use of extension services and agricultural training were found to be positively correlated to technical efficiency for both models, however, mixed evidence was found for receiving subsidies. These correlations are only partly confirmed by the results of the error components estimation: Here both the unconstrained as well constrained model specification agree on a negative effect on efficiency by the use of insecticides, the use of extension services, and receiving subsidies. Mixed evidence was found for the use of herbicides, the application of commercial seeds, and the use of agricultural training. It can be concluded for this part of the analysis that only with respect to the use of insecticides all model specifications agree on the negative efficiency effect.

The reported efficiency results of the unconstrained as well as constrained model specification point to the relevance of theoretical consistency of the estimated frontier. As outlined in section 3 model II differs from model I by applying a matrix decomposition technique to impose concavity on the translog cost frontier to ensure functional regularity and finally the adherence to the basic microeconomic principle of cost minimization (see Sauer 2005). Table 8 delivers the relative differences in the efficiency scores for the unconstrained and the constrained specification.

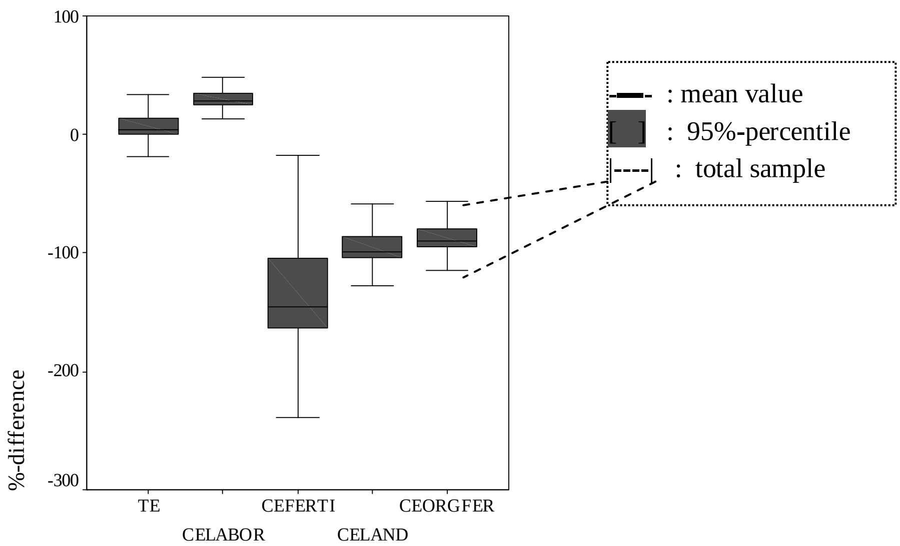
Table 8. Relative Difference in Efficiency Scores Uncontrained VS. Constrained Specification

MEASURE	MEAN (%)[2]	STDERR[1]	MIN	MAX
TECHNICAL EFFICIENCY	7.36	12.14	-18.06	41.45
COST EFFICIENCY LABOUR	30.52	8.15***	13.25	53.00
CE FERTILIZER	-131.41	51.49**	-239.19	11.85
CE LAND	-94.09	16.06***	-127.71	-49.41
CE ORGANIC FERTILIZER	-86.62	13.63***	-115.14	-48.70

1: *,**,*** significance at the 1, 5, and 10% level.

The relative difference in the efficiency scores in absolute terms ranges at average from about 7.4% (producer-specific technical efficiency measure) to about 131.4% (producer- and input-specific cost efficiency measure for organic fertilizer). Hence, this is empirical evidence for the validity of our concerns about the appropriate functional form and its theoretical consistency (see Sauer 2005). Figure 1 illustrates these differences with respect to the single efficiency measure.

Figure 1. Percentile and Mean Differences in Efficiency by Imposing Curvature Correctness



Finally the results of the applied bootstrapp procedure confirmed the estimates for the theoretically consistent model (model II) on the estimation stage of the error-components specification (see also table A5).

6. Summary and Implications

This study focuses on the relative efficiency of small-scale maize farmers in Romania by using a cost function modelling framework combining the stochastic frontier approach of shadow prices as well as the mainstream error components model. Various market distortions are adressed by adopting the concept of a shadow cost frontier delivering insights in the systematic input specific allocative efficiency. After correcting for shadow prices we subsequently reveal evidence on farm specific technical efficiency and develop an efficiency index for a sample of Romanian maize producers in 2002. Finally different transition policy relevant factors are investigated with respect to their impact on technical efficiency on group as well as individual farm level. By referring to the ongoing discussion on functional consistency of the stochastic frontier with respect to microeconomic theory we formulated two basic model specifications – one without and one with functional concavity imposed - and estimated the individual cost system by means of iterated seemingly unrelated regression techniques (ITSURE).

The empirical results show that price distortions prevail in the agricultural input markets in the Romanian economy and that a model incorporating such market distortions seems to be more suitable in an agricultural transition context than one solely based on observable market price ratios. The estimated shadow parameters for the quasi-fixed inputs revealed that the farms' resource endowment – i.e. land endowment as well as livestock size – crucially influences its relative allocative performance. A high technical efficiency on farm level with a moderate variation over the sample was found but relatively poor scores on systematic allocative efficiency. With respect to group-wise technical efficiency the empirical results for the shadow frontier show that the use of herbicides, the use of insecticides, and the application of commercial seeds are negatively correlated with the technical efficiency of the maize farmers. This suggests that there is a need for policy measures targeting an efficiency improvement of with respect to the application processes (i.e. technology) due to chemicals as well as seeding. On the other side positive efficiency gains can be reported for the use of extension services as well as agricultural training on the farm level suggesting further engagement by the political actors in these areas. However, the results of the error components estimations only partly confirm those policy implications. Overall, all model specifications agree only with respect to the use of insecticides on the negative effect on efficiency by an additional usage of such chemicals. The revealed relative difference in the efficiency scores of up to 240% on the individual farm level as a consequence of the imposition of curvature correctness confirmed the relevance of theoretically consistent modelling with respect to the stochastic measurement of efficiency. The empirical applications hence document the need for a posteriori checking the regularity of the estimated frontiers by the researcher and, if necessary, the a priori imposition of the theoretical requirements on the estimation models (see Sauer 2005).

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Appendix

Table A1. Parameter Estimates Shadow Cost Frontier – Model I

Cost Function					
PARAMETER	ESTIMATE	STERR	PARAMETER	ESTIMATE	STERR
α_0	250.378	0.014***	$\delta_{laborgf}$	0.012	3.922E-05***
α_{lab}	6.246	0.007***	$\delta_{fertland}$	-0.112	0.004***
α_{fert}	-5.246	0.006***	$\delta_{fertorgf}$	-0.003	3.923E-05***
γ_y	0.031	0.007***	δ_{yland}	0.010	0.002***
α_{lablab}	0.002	0.009	δ_{yorgf}	-0.006	0.001***
$\alpha_{fertfert}$	0.112	0.010***	χ_{herb}	0.024	0.011**
γ_{yy}	-1.062	0.013***	χ_{insect}	0.022	0.013
$\beta_{labfert}$	-0.115	0.009***	χ_{seed}	0.013	0.009
β_{ylab}	-0.029	0.009***	χ_{subs}	-0.018	0.008**
β_{yfert}	0.029	0.012**	χ_{ext}	-0.025	0.009**
δ_{land}	4.984	0.007***	χ_{train}	-0.029	0.013**
δ_{orgf}	0.074	0.006***	θ_{lab}	0.476	0.007***
$\delta_{landland}$	-0.036	0.006***	θ_{fert}	0.138	0.006***
$\delta_{orgforgf}$	-0.005	0.014	θ_{land}	0.381	0.001***
$\delta_{landorgf}$	0.004	0.001***	θ_{orgf}	0.259	0.001***
$\delta_{labland}$	0.219	0.001***			
ADJR^2	0.507				
F-VALUE	228E+04				
P>|F|	8.253E-182				
CONCAVITY (%)	26.56				

*,**,***: significance at 10,5, and 1 % -level.

Labor Share					
PARAMETER	ESTIMATE	STERR			
α_{lab}	25.292	0.001***			
α_{fert}	0.002	0.001			
$\beta_{labfert}$	18.676	0.002***			
β_{ylab}	26.702	0.002***			
β_{yfert}	2.345	0.003***			
δ_{land}	-7.089	0.001***			
δ_{orgf}	-11.594	0.001***			
$\delta_{landorgf}$	-62.773	2.742E-04***			
$\delta_{labland}$	-144.574	8.919E-04***			
$\delta_{laborgf}$	-0.216	8.987E-06***			
δ_{yland}	-0.065	5.12E-04***			
$\delta_{fertland}$	13.923	8.918E-04***			
$\delta_{fertorgf}$	-0.041	0.003***			
δ_{yorgf}	-0.006	0.001***			
θ_{lab}	0.476	0.007***			
θ_{fert}	0.138	0.006***			
θ_{land}	0.381	0.001***			
θ_{orgf}	0.259	0.001***			
ADJR^2	0.848				
F-VALUE	1516.944				
P>|F|	4.145E-76				

*,**,***: significance at 10,5, and 1 % -level.

Table A2. Parameter Estimates Error Components Frontier – Model I

Cost Function					
PARAMETER	ESTIMATE	STERR	PARAMETER	ESTIMATE	STERR
α_0	1.093	0.021***	δ_{orgf}	0.083	0.008***
α_{lab}	0.086	0.015***	$\delta_{landland}$	-0.036	0.038
α_{fert}	0.157	0.032***	$\delta_{orgforgf}$	0.005	4.614E-04***
γ_y	-0.058	0.016***	$\delta_{landorgf}$	-0.001	0.003
α_{lablab}	-0.025	0.003***	$\delta_{labland}$	0.005	0.014
$\alpha_{fertfert}$	-0.001	0.025	$\delta_{laborgf}$	-4.868E-04	7.618E-04
γ_{yy}	-4.835E-0.4	0.005	$\delta_{fertland}$	0.014	0.052
$\beta_{labfert}$	0.010	0.015	$\delta_{fertorgf}$	5.018E-04	0.003
β_{ylab}	-0.005	0.007	δ_{yland}	0.005	0.038
β_{yfert}	0.061	0.036*	δ_{yorgf}	-0.004	0.001***
δ_{land}	-0.039	0.029			
$\ln\sigma^2_v$					
β_0	-7.042	0.366***			
$\ln\sigma^2_u$					
χ_{herb}	2.113	0.972*	χ_{ext}	0.435	0.698
χ_{insect}	5.280	1.596***	χ_{train}	3.172	0.839***
χ_{seed}	0.401	0.814	χ_{subs}	3.112	1.057***
σ_v	0.029	0.005***			
WALDCHI^2(20)	2558.20				
LL	105.356				
P>CHI^2	0.000				

*,**,***: significance at 10,5, and 1 % -level.

Table A3. Parameter Estimates Shadow Cost Frontier – Model II

Cost Function					
PARAMETER	ESTIMATE	STERR	PARAMETER	ESTIMATE	STERR
α_0	-1.064	0.021***	$\delta_{laborgf}$	-0.007	5.81E-05***
α_{lab}	0.197	0.010***	$\delta_{fertland}$	-0.192	0.006***
α_{fert}	0.803	0.009***	$\delta_{fertorgf}$	-0.004	5.809E-05***
γ_y	0.002	0.010	δ_{yland}	0.104	0.003***
α_{lablab}	0.022	0.015	δ_{yorgf}	0.001	4.27E-04***
$\alpha_{fertfert}$	0.093	0.015***	χ_{herb}	0.042	0.016**
γ_{yy}	-3.802	0.019***	χ_{insect}	0.008	0.020
$\beta_{labfert}$	-0.115	0.013***	χ_{seed}	0.024	0.013*
β_{ylab}	0.032	0.014**	χ_{subs}	0.036	0.038
β_{yfert}	-0.032	0.018*	χ_{ext}	-0.051	0.015***
δ_{land}	0.193	0.009***	χ_{train}	-0.087	0.019***
δ_{orgf}	-0.003	0.009	θ_{lab}	0.320	0.010***
$\delta_{landland}$	0.089	0.009***	θ_{fert}	0.585	0.009***
$\delta_{orgforgf}$	-0.006	0.020	θ_{land}	1.987	0.001***
$\delta_{landorgf}$	-0.001	0.002	θ_{orgf}	0.292	0.002***
$\delta_{labland}$	0.045	6.19E-04***	h_{11}	-0.137	0.015
			h_{22}	-0.065	0.015***
			h_{33}	-0.067	0.009***
			h_{44}	-0.003	0.020
			h_{12}	0.044	0.013***
			h_{13}	0.083	6.19E-04***
ADJR^2	0.703		h_{14}	-0.007	5.81E-05***
F-VALUE	-330.448		h_{23}	-0.036	0.006***
P>|F|	4.048E-59		h_{24}	-0.006	5.809E-05***
CONCAVITY (%)	79.69		h_{34}	-0.001	0.002

*,**,***: significance at 10,5, and 1 % -level.

Labor Share					
PARAMETER	ESTIMATE	STERR			
α_{lab}	-25.603	0.060***			
α_{fert}	18.935	0.055***			
$\beta_{labfert}$	-50.102	0.079***			
β_{ylab}	-67.346	0.086***			
β_{yfert}	10.841	0.107***			
δ_{land}	-514.971	0.054***			
δ_{orgf}	2.629	0.054***			
$\delta_{landorgf}$	136.857	0.010***			
$\delta_{labland}$	58.338	0.034***			
$\delta_{laborgf}$	9.227	34.6E-04			
δ_{yland}	92.592	0.019***			
$\delta_{fertland}$	1862.736	0.034***			
$\delta_{fertorgf}$	-2876.135	0.121***			
δ_{yorgf}	0.001	4.27E-04***			
θ_{lab}	0.320	0.010***			
θ_{fert}	0.585	0.009***			
θ_{land}	1.987	0.001***			
θ_{orgf}	0.292	0.002***			
ADJR^2	0.621				
F-VALUE	1.024				
P>|F|	0.444				

*,**,***: significance at 10,5, and 1 % -level.

Table A4. Parameter Estimates Error Components Frontier – Model II					
Cost Function					
PARAMETER	**ESTIMATE**	**STERR**	**PARAMETER**	**ESTIMATE**	**STERR**
α_0	1.119	0.067***	δ_{orgf}	-0.080	0.052*
α_{lab}	-0.029	0.038	$\delta_{landland}$	-1.335	0.358***
α_{fert}	0.102	0.224	$\delta_{orgforgf}$	-0.008	0.007
γ_y	0.015	0.055	$\delta_{landorgf}$	-0.011	0.030
α_{lablab}	-0.064	0.008***	$\delta_{labland}$	0.029	0.0648
$\alpha_{fertfert}$	0.332	0.379	$\delta_{laborgf}$	-0.004	0.004
γ_{yy}	0.086	0.012***	$\delta_{fertland}$	-0.352	0.613
$\beta_{labfert}$	0.148	0.077*	$\delta_{fertorgf}$	-0.018	0.036
β_{ylab}	-0.045	0.016***	δ_{yland}	0.114	0.178
β_{yfert}	-0.006	0.204	δ_{yorgf}	0.019	0.007***
δ_{land}	-0.013	0.189			
$\ln \sigma^2_v$					
β_0	-5.273	0.275***			
$\ln \sigma^2_u$					
χ_{herb}	-1.612	0.671**	χ_{ext}	1.722	0.609***
χ_{insect}	16.401	0.719***	χ_{train}	2.531	0.687***
χ_{seed}	-0.603	0.624	χ_{subs}	-1.201	0.751*
σ_v	0.072	0.010***			
WALDCHI^2(20)	2101.49				
LL	53.256				
P>CHI^2	0.000				

*,**,***: significance at 10,5, and 1 % -level.

Table A5. Bootstrapped Estimates Error Components Frontier II

VARIABLE	OBSERVED	STERR	[0.05	0.95]
[LNCEST]				
α_0	1.130	0.226***	0.673	1.588
α_{lab}	-0.026	0.101	-0.229	0.176
α_{fert}	0.137	0.431	-0.733	1.007
γ_y	0.016	0.177	-0.342	0.374
α_{lablab}	-0.063	0.017***	-0.098	-0.029
$\alpha_{fertfert}$	0.236	0.481	-0.735	1.208
γ_{yy}	0.085	0.056*	-0.029	0.198
$\beta_{labfert}$	0.165	0.190	-0.219	0.549
β_{ylab}	-0.042	0.053	-0.149	0.065
β_{yfert}	-0.111	0.307	-0.732	0.509
δ_{land}	-0.023	0.625	-1.285	1.239
δ_{orgf}	-0.085	0.132	-0.351	0.181
$\delta_{landland}$	-1.547	0.338***	-2.230	-0.864
$\delta_{orgforgf}$	-0.009	0.017	-0.043	0.025
$\delta_{landorgf}$	-0.026	0.068	-0.163	0.112
$\delta_{labland}$	0.016	0.132	-0.251	0.283
$\delta_{laborgf}$	-0.004	0.012	-0.028	0.019
$\delta_{fertland}$	0.201	0.282	-0.369	0.772
$\delta_{fertorgf}$	0.019	0.019	-0.019	0.058
[LNSIG2V]				
β_0	-5.240	10.992	-27.438	16.959
χ_{herb}	-1.615	6.621	-14.986	11.755
χ_{insect}	16.589	13.441*	-10.556	43.734
χ_{seed}	-0.635	4.797	-10.322	9.053
χ_{subs}	-1.236	7.226	-15.829	13.357
χ_{ext}	1.702	5.246	-8.892	12.297
χ_{train}	2.516	6.436	-10.482	15.514
[LNSIG2U]				
β_0	-34.733	23.706*	-82.609	13.143

*,**,***: significance at 10,5, and 1 % -level.

Figure A1. Producer Specific Technical Efficiency I – Density Distribution

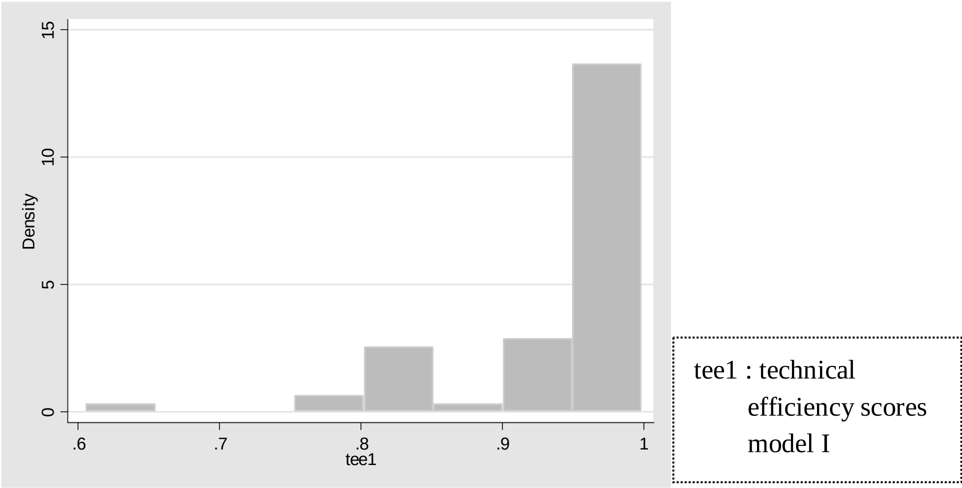
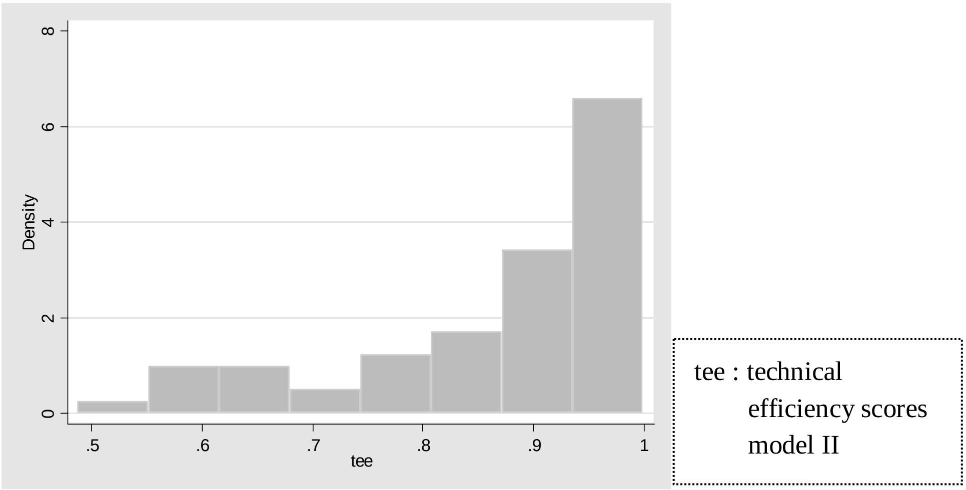


Figure A2. Producer Specific Technical Efficiency II – Density Distribution



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